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An analytic hierarchy process augmented with expert rules for product driven control in cyber-physical manufacturing systems

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A B S T R A C T

In Cyber-Physical Manufacturing Systems (CPMS), numerous distributed control architectures were suggested to make different production entities active with respect to decision-making and control processes, so that they can process information, interact, and make control decisions in an autonomous and adaptive way. Nevertheless, developing Product-Driven Control (PDC) mechanisms that enable Smart Products (SPs) to make control decisions to cope with disturbances is still a complex, open-ended, and challenging problem. This article suggests a PDC approach that enables SPs to learn how to make control decisions to react to disturbances and maintain continuity of operations. The control mechanism involves an Analytic Hierarchy Process (AHP) augmented with Expert rules to cope with the limitations of standard AHP in dealing with dynamic problems. The mechanism is applied to a dispatching problem in an industrial scale assembly process. A multi-agent discrete event simulation model is used to create a set of normal and disturbed production scenarios. SP agents use context indicators and performance assessment to activate Expert rules and update AHP preferences and scales before making dispatching control decisions to react to disturbances. Data analytics tools are developed to help manufacturing system Experts define and fine-tune rules, based on rule firing statistics and corresponding context indicators and performance assessment acquired from simulation. Experimentations and results show competitive performance and highlight interesting research directions.

Keywords:

Cyber-Physical Manufacturing Systems
Distributed control
Smart products
Disturbances
Analytic Hierarchy Process
Expert supervised learning
Multi-agent simulation

1. Introduction

The new developments in the industry 4.0 paradigm and technologies have led to the emergence of Cyber-Physical Manufacturing Systems (CPMS), which take advantage of digitalization and automation at multiple levels within a factory and across the enterprise to enable higher productivity, higher quality, and lower costs (Napoleone et al., 2020). CPMS promote the concept of “activeness” of smart production entities (e.g., devices, machines, products, and augmented operators). This concept is closely related to autonomous behaviour and to participation in decision-making and control

processes (Sallez et al., 2010). In this way, smart entities become able to interact with each other and with Enterprise Information Systems (Romero and Vernadat, 2016), to handle data, information and knowledge (Aven, 2013), and to make control decisions in more autonomous, adaptive and resilient ways (Napoleone et al., 2020).

Despite the advanced capabilities that CPMS offer, these systems are still faced with complex challenges, mainly related to change management at design and operational stages (Panetto et al., 2019). At design stage, change is related to fast-paced technological evolution, and to managing changes in functional (e.g., mass-customization and servitization) and non-functional (e.g., performance and resilience) requirements of both engineered products, processes and services. This article focuses on changes at operational stage, which are related to disturbances that may disrupt the continuity of flows and operations. Examples of such disturbances include supply or demand uncertainty, resource unavailability and/or resource unreliability (Attajer et al., 2019; Chaabane and Trentesaux, 2019; Sanchis and Poler, 2019). Dealing with disturbances appropriately is

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important, because otherwise, they can cause detrimental consequences, including both direct impacts and probable propagation. Disturbances potentially reduce productivity and cost-effectiveness, increase safety risks for production resources, disrupt the continuity of operations and business, in addition to disrupting financial and information flows in supply chains, therefore putting entire organizations at risk. As highlighted in a field survey by (Bokrantz et al., 2016), dealing with production disturbances effectively and efficiently is vital for both survival and competitiveness.

Indeed, distributed control architectures, where information processing is distributed, and decision-making is decentralized over several smart production entities offer innovative mechanisms to control disturbances and operational risks (Derigent et al., 2020; Valckenaers, 2020). Unfortunately, only a few works succeeded in decentralizing control capabilities on SPs to enable them to play more active roles in decisional processes, particularly to react to disturbances and operational risks in an autonomous and adaptive way, while maintaining performance at acceptable levels. To fill in this gap, this article develops a Multi-Criteria Decision-making (MCDM) control mechanism, based on an Analytic Hierarchy Process Augmented with Expert rules (A-AHP) to enable SPs to make control decisions to react to disturbances and maintain continuity of operations. Therefore, Section 2 analyses the related literature to better position the contributions of this article. Section 3 details the suggested approach. Section 4 introduces a case study application of our approach. Experiments and results are discussed in Section 5. Finally, the Section 6 provides a conclusion and opens several future research directions.

2. Related works

Manufacturing control systems and architectures are generally classified into centralized, decentralized and hybrid control architectures (Meissner et al., 2017; Trentesaux, 2009). Each class has its own advantages and limitations, and therefore, the selection of a class over another will depend more on the requirements set by manufacturing system experts, and on their expectations regarding the manufacturing system behaviour and performance (Jaskó et al., 2020). Whereas centralized control offers global optimization opportunities, it suffers scalability, flexibility and reactivity limitations. Several recent research streams suggest the advantages and benefits of autonomous control concepts compared to traditional centralised approaches (Antons and Arlinghaus, 2022). Unfortunately, existing manufacturing control systems and architectures still offer limited capabilities with respect to the management of disturbances and risks (Bayar et al., 2015, 2016; Darmoul et al., 2013). Volatility, Uncertainty, Change and Ambiguity (VUCA) in manufacturing environments motivate orienting this article towards autonomous distributed control for the sake of increased flexibility, reactivity and ultimately, resilience (Mack et al., 2015).

Dealing with disturbances and risks is achieved by complementary approaches in industry and academy, each with its own advantages and limitations. Industrial practice focuses more on developing Intelligent Manufacturing Execution Systems (MES) to monitor operations, improve real-time context awareness, and therefore support advised decision-making and control (Shojaeinasab et al., 2022). However, MES still lack specific functions, dedicated to disturbance and risk management, while being sufficiently generic to enable dealing simultaneously and comprehensively with many types of disturbances and risks (Bayar et al., 2015, 2016; Darmoul et al., 2013).

The control of manufacturing systems encompasses planning, scheduling, dispatching, and routing decisions (Wu, 2014). Scheduling tends to be increasingly sensitive to real-time events, which intensifies an already existing trend towards real-time monitoring and dispatching due to proliferation of sensing and data-driven

technologies (Parente et al., 2020). This article develops an approach and illustrates it on the dispatching process, defined as “the activity to assign the next job to be processed from a set of jobs awaiting service” (Wu, 2014). Although robust or predictive scheduling approaches are possible to consider the available information on future jobs (Echsler Minguillon and Stricker, 2020), this article focuses on reactive control to promote autonomy, flexibility and reactivity through the decentralization of control decision-making over SPs. Therefore, the approach suggested in this article exploits the synergy of three domains: Product-Driven Control (PDC), Machine Learning in PDC, and the Analytic Hierarchy Process (AHP). The following sub-sections review some specific aspects of literature on these three topics.

2.1. Product-driven control

PDC is relevant to distributed artificial intelligence, which can be developed through the agent, holonic, or else bionic frameworks (Antons and Arlinghaus, 2022; Derigent et al., 2020; Leitão, 2009; Trentesaux, 2009). Whereas considerable research focused on distributing control over smart resources, relatively fewer research addressed distribution on SPs (Antons and Arlinghaus, 2022; Derigent et al., 2020). Several references discussed different definitions, classifications, levels of, and frameworks for, product “smartness” and “intelligence” (McFarlane et al., 2013; Meyer et al., 2009; Sallez, 2014; Wuest et al., 2018). PDC is closely related to the concepts of “smart products” and “holonic manufacturing” (Meyer et al., 2009; Valckenaers, 2020). In (Derigent et al., 2020), the authors highlighted that product intelligence in existing Holonic Control Architectures (HCA) refers mainly to data management and interoperability capabilities for the traceability of product evolution throughout its lifecycle. The authors particularly emphasized that only a few existing HCA study decentralized PDC mechanisms and architectures at manufacturing stage (Lenz et al., 2020). This is further emphasized in (Kovalenko et al., 2019), where the authors investigated several product-driven HCA and multi-agent control architectures regarding decision-making and stressed that there is still room for developing product agents that use intelligent mechanisms to make decisions.

2.2. Artificial intelligence (AI) and machine learning (ML) in PDC

Despite exhaustive reviews of AI and ML techniques applied to production planning and control literature, several recent surveys failed to identify applications to promote activeness of SPs with respect to decision-making and control processes (Antons and Arlinghaus, 2022; Bertolini et al., 2021; Bueno et al., 2020; Parente et al., 2020), which provides an extra motivation for this article to develop product embedded control mechanisms.

Dispatching problems are traditionally addressed using reactive approaches, where no decision is taken in advance (Echsler Minguillon and Stricker, 2020). Instead, immediate and local decisions are made in the presence of real-time events, usually based on simple heuristics, such as Dispatching Rules (DR) (e.g. FIFO and shortest processing time), to prioritise jobs waiting to be processed in waiting lines and resource queues. DR are traditionally derived by empirical or analytical studies, sustained by scheduling theory. As simple sequencing procedures, DR are flexible, easy to implement, and extremely fast to execute. However, their performance is still limited, and depends heavily on the context (Ferreira et al., 2021). Traditional DR are neither adaptive, nor self-learning, nor else flexible enough to be effective under Industry 4.0 (Parente et al., 2020). The dispatching is made from the perspective of smart resources, waiting lines and queueing systems, rather than from the perspective of SPs, which are considered passive, and do not participate actively in decision-making and control processes.

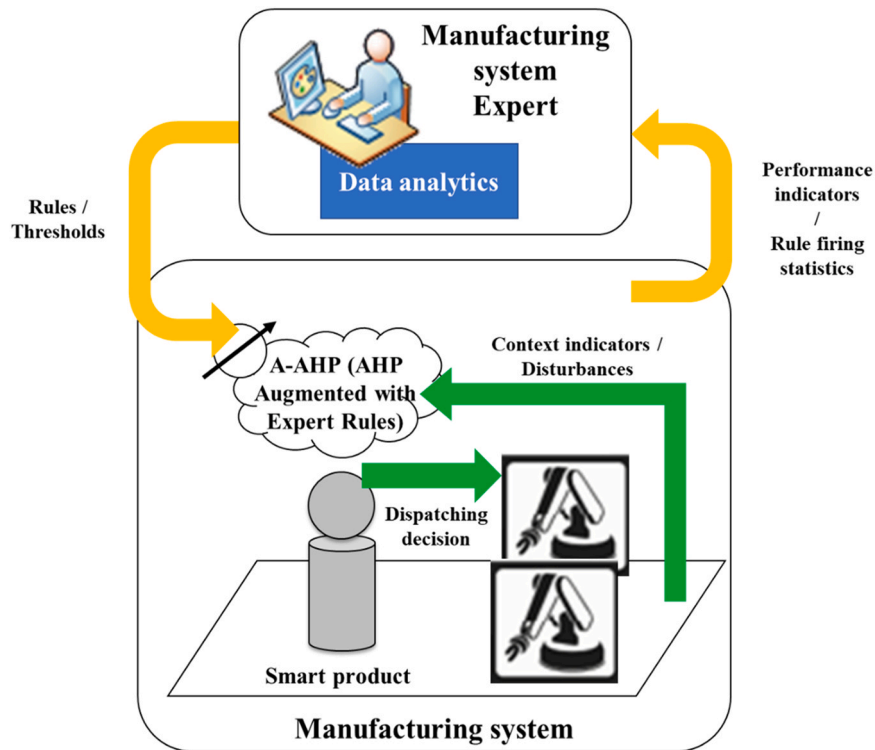


Fig. 1. General framework of investigation.

Indeed, AI and ML were used to boost the effectiveness of DR. However, the suggested approaches make use of complex, black-box models, such as Neural Networks and tree ensembles, that are harder to interpret and manipulate by human decision makers. These models are designed and validated with little domain expertise. Users can only observe the input-output relationships, thus missing the underlying reasons or processes to produce the outputs, which makes them uncomfortable and non-confident in the obtained results. Therefore, with black-box models, decision-makers are forced to sacrifice transparency, traceability and accountability in exchange of some expected performance in dealing with complex problems. As a result, despite their good behaviour in some tested cases, DRs frequently do not generalise well to unseen scenarios (Ferreira et al., 2021).

To alleviate this limitation, some references suggest to gather knowledge about real time manufacturing contexts, and to use it to generate new and improved knowledge from which better dispatching strategies may come to light (Ferreira et al., 2021; Parente et al., 2020; Zhang et al., 2022). Unfortunately, in such references, products are usually passive and they do not make their own decisions.

2.3. Analytic hierarchy process

Decision problems at manufacturing stages are multicriteria by essence because decisions can be rarely evaluated in terms of a single criterion. Time impacts, cost consequences, and quality outcomes all need to be considered when making decisions at manufacturing execution stages. In this article, the AHP is chosen among many existing MCDM techniques (Figueira et al., 2005), because of its relative simplicity, ease of use, and great flexibility compared to other MCDM techniques (Ho and Ma, 2018) (a more detailed justification is provided in the beginning of Section 3). In (Trentesaux et al., 1998), AHP was interfaced with Human Experts to handle conflicting objectives in a task allocation problem. AHP was

distributed only on Resource Holons in (Ounnar and Ladet, 2004; Ounnar and Pujo, 2012; Pujo et al., 2009). In (Derigent et al., 2017), a two-stage AHP-based algorithm was suggested to handle unexpected machine breakdowns. The first stage determines which kind of strategy the product should adopt, while the second stage selects the most appropriate resource to fulfill the product requirements. The assessments of decisions are entrusted to products through preference functions. Unfortunately, these functions are not adaptive, which limits the system's capability to respond to dynamic changes. Although AHP has been studied extensively in literature (Ho and Ma, 2018; Khaira and Dwivedi, 2018), it has been used only scarcely in holonic/multi-agent manufacturing control (Derigent et al., 2020), and it has not yet been adapted to enable SPs to learn how to make control decisions in disturbed contexts.

The analysis of literature shows that lots of efforts were dedicated to make resources smart, and relatively less effort was dedicated to make products active with respect to decision-making and control processes. When dealing with SPs, the focus is put more on product-embedded data management capacities throughout a product lifecycle, and less on decision-making and control capabilities, particularly to enable them to react to disturbances and operational risks in an autonomous and adaptive way, while maintaining performance at acceptable levels. Achieving product smartness and activeness in terms of decision-making and control processes is important because it enforces product autonomy, contributes to increasing system flexibility and reactivity, and enhances system awareness, responsiveness, and resilience to disturbances and risks.

3. Suggested control approach

The main contribution of this article lies at the crossroad of the three previously reviewed topics (i.e. PDC, ML and AHP). An approach is developed based on a hierarchical framework, which is illustrated on the dispatching process, as depicted in Fig. 1.

3.1. A product-driven control

Architecture is adopted to promote activeness of SPs with respect to decision-making and control processes, particularly to react to disturbances and maintain continuity of operations. A reactive approach is considered, where no prior knowledge is available or predicted on future arrivals of products. Instead, as soon as customer orders arrive, SPs are released into the manufacturing system according to a pre-established allocation planning, which then needs to be adapted according to manufacturing system context and disturbances.

3.2. Machine learning

Manufacturing system experts delegate dispatching control responsibilities to SPs. This delegation is achieved through the definition and provision of rules and thresholds that enable adapting preferences of control decisions.

3.3. Multi-criteria decision-making

In case of disturbances, each SP has to adapt its pre-established allocation planning by selecting a decision from a set of available control decisions. To achieve this selection, multi-criteria decision-making is used based on an AHP mechanism augmented with the expert rules.

AHP is appealing to decision makers because it offers an intuitive hierarchical evaluation and weighting process, mainly based on iterative and sequential pairwise comparisons between a set of available alternatives (i.e. dispatching control decisions) (Saaty, 1994), which contribute to a human-scale management of the complexity of the dispatching control problem. It is this human-scale management knowledge that will be delegated to SPs through AHP to enable PDC. Moreover, manufacturing experts are generally more comfortable and biased towards decision-making processes that are directly related to product performance, because it directly relates to customer satisfaction. Manufacturing experts are less comfortable with decisions and performance that are resource and queueing system oriented, which is the case of classical dispatching rules. This notice motivates providing SPs with MCDM capabilities to actively select the next resource that will provide the required service in a way that is adaptive to the manufacturing system context, particularly in case of occurrence of disturbances and risks.

In this article, Rules provide an explicit way to augment AHP and adapt it to the dispatching problem. The Augmented AHP (A-AHP) provides an explicit way to explain and trace how decisions were made. To the best of the authors' knowledge, no other article in literature uses such combination to enable PDC.

3.4. Supervised learning approach

In Fig. 1, it is interesting to notice two loops:

- An orange loop, involving the manufacturing system Expert, and enabling him/her to refine his/her knowledge and expectations, and to transfer them to SPs through the definition of rules.
- A green color loop, involving SPs, and enabling them to make decisions using the set of defined and refined rules.

The hierarchical framework of Fig. 1 is further detailed in Fig. 2. Expert rules are refined through data analytics and supervised learning, and embedded in SPs through the suggested A-AHP mechanism. Simulation is used to create different scenarios of production and disturbances.

1. First, the manufacturing system Expert sets the thresholds and provides rules to enable the SPs to adapt preferences among dispatching control decisions (arrow notated 1a in Fig. 2). These thresholds and rules are embedded in SPs for decision-making. The Expert also sets the production scenarios to be simulated (arrow notated 1b in Fig. 2).
2. Each SP follows its pre-established allocation planning to complete its service list. A SP collects context and performance indicators (arrow notated 2 in Fig. 2). Two cases are then considered:
 - If no disturbance is detected, the default planned resource is considered as destination to receive the next service.
 - If a disturbance is detected, the SP runs the A-AHP and the best ranked resource is selected to receive the next service.
3. The decision about the selected destination resource is sent to the simulation environment to update product routings (arrow notated 3 in Fig. 2).
4. By the end of a simulated scenario, statistics are collected (e.g., number of times a rule was fired and corresponding performance indicators), and sent to a data analytics tool (arrow notated 4 in Fig. 2).
5. Feedback about rule statistics and performance indicators is shown to the manufacturing system Expert, who performs data analytics (arrow notated 5 in Fig. 2) to update thresholds and rules.

This cycle is repeated until a set of satisfactory thresholds and rules is obtained.

3.5. AHP augmentation with expert rules

AHP allows ranking a finite set of available dispatching control decisions according to multiple criteria and based on sets of pairwise comparisons. Fig. 3 shows in white color, the steps of the standard AHP procedure, which has some core limitations. It is worth noticing that the evaluations of preferences of criteria (cf. STEP30) are subjective, as they depend on the type of industry and the decision-maker expertise, while preferences of decisions (cf. STEP40) do not reflect time, state, dynamics and disturbance context of the manufacturing system. They are set manually and permanently by decision makers. Unfortunately, as manufacturing systems are dynamic, state and context are not static, which means that these evaluations need to be adapted before applying the ranking mechanisms. Adapting AHP parameters manually is time consuming and is not suitable to the dynamics of automated systems. If parameter calibration is kept manual, it would slow down the decision-making and reaction processes, with the risk that resulting decisions are not well tailored to disturbance context, and to system state and dynamics. These limitations inhibit the autonomy and reactivity of SPs to cope with different disturbances and may lead to deadlocks and poor performance.

Therefore, Fig. 3 shows the new steps that were added in red color to obtain the suggested A-AHP mechanism. The following subsections provide a detailed description of each step.

3.5.1. Notations

This section introduces the set of notations that are used later and sorted alphabetically:

- $A = (a_{n,o})_{N \times N}$: square N by N matrix of preferences between criteria, regardless of control decisions.

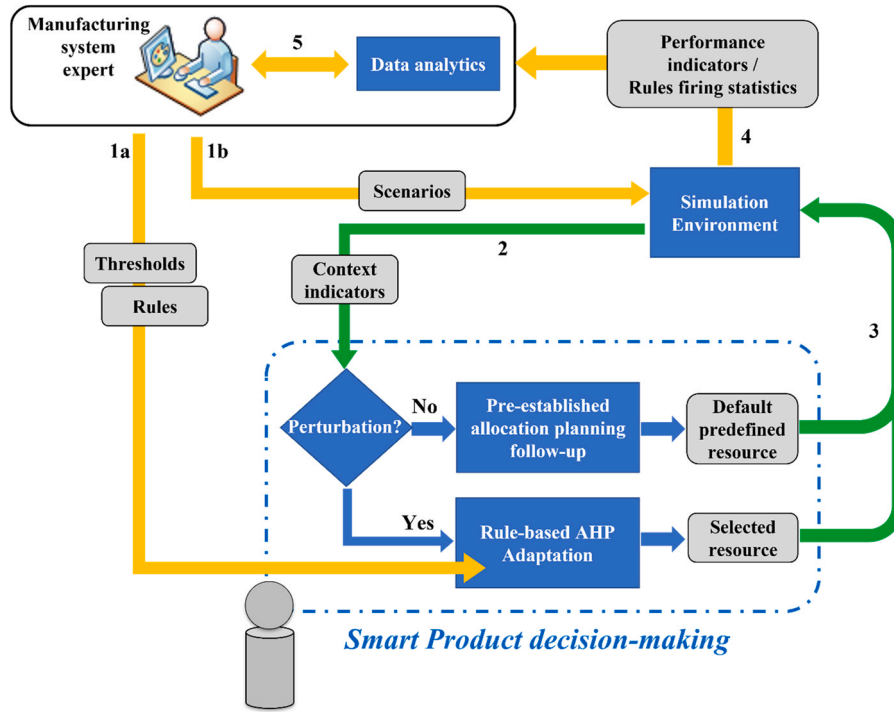


Fig. 2. Supervised learning approach.

- $B_{C_n} = (b_{m,p})_{C_n}$: square M by M matrix of preferences of control decisions with respect to criterion C_n .
- C_n : a set of N criteria to evaluate and rank control decisions, indexed by $n \in \{1, \dots, N\}$.
- CR: consistency ratio.
- CSRL: average cost of staying in the *reference loop*.
- D_m : set of M control decisions, indexed by $m \in \{1, \dots, M\}$.
- F_{C_n, D_m, D_p} : function involving a set of indicators used to compare decision D_m to D_p with respect to criterion C_n .
- FR_{R_i} : failure rate of resource R_i .
- LC: logistic cost; when the product decides to go to an alternative resource, an additional logistic cost is added.
- $MinThreshold_{C_n}$: minimum thresholds on scales of relative importance of criterion C_n .
- $MaxThreshold_{C_n}$: maximum thresholds on scales of relative importance of criterion C_n .
- P_l : set of L products, indexed by $l \in \{1, \dots, L\}$.
- PT_{R_i} : processing time on resource R_i .
- PC_{R_i} : production cost on resource R_i .
- R_i : set of I resources, indexed by $i \in \{1, \dots, I\}$.
- RPT_{R_i} : required time to achieve a service on resource R_i .
- S_j : set of J services provided by resources, indexed by $j \in \{1, \dots, J\}$.
- $Thr_RPT_{R_i}$: thresholds on the required time RPT_{R_i} .
- $Thr_TTF_{R_i}$: thresholds on the time to failures of resource R_i .
- TTF_{R_i} : time to failure of resource R_i .
- TTR_{R_i} : time to repair of resource R_i .
- U_k : set of K disturbances, indexed by $k \in \{1, \dots, K\}$.
- w_{C_n} : weight vector of preferences with respect to criterion C_n .
- w_{D_m, C_n} : weight vector of decision preferences with respect to criterion C_n .
- w_D : weight vector of decision preferences with respect to all criteria.
- WTQ_{R_i} : average waiting time of products in the queue of resource R_i .

- $WTRL$: average waiting time of products in the *reference loop*.

3.5.2. STEP00 – product and production system characteristics

This step defines the manufacturing system specificities and flexibilities (e.g., main and alternative routings, equivalent resources), as well as the SP agents' representation of their environment, which enables them to interact with Enterprise Information Systems to get suitable updates about system parameters and data (e.g., arrival rates, failure rates, tolerable delays). Fig. 4 provides an abstract view of a manufacturing system.

3.5.2.1. Resources and associated services. Resources are automated or semi-automated value-adding nodes, located around a routing network. According to the PDC approach, the resources are considered as passive entities that only provide services on request, without any decisional capabilities (Trentesaux and Thomas, 2013). A resource delivers a set of services with different service times. Some services can be delivered by several resources, considered as redundant. A waiting area is associated to each resource, assumed to be finite, with a FIFO rule. Resources have limited reliability and are subject to disturbances, which have direct impacts on the resources quality of service.

3.5.2.2. Routing network. The routing network is modeled as a strongly connected directed graph able to connect the different resource nodes. A specific routing loop, called the *reference loop*, is used to loop products, such as those waiting for availability of a critical resource. On this *reference loop* are placed *decisional nodes*, where products must decide which resource to select to provide the next service in case of a disturbance. A transportation system is associated with the routing network to achieve internal logistics. It is assumed to be capacity limited (e.g., limited number of conveying systems) and reliable (e.g., fixed transportation times, no breakdowns, and no maintenance tasks that forbid the use of specific arcs).

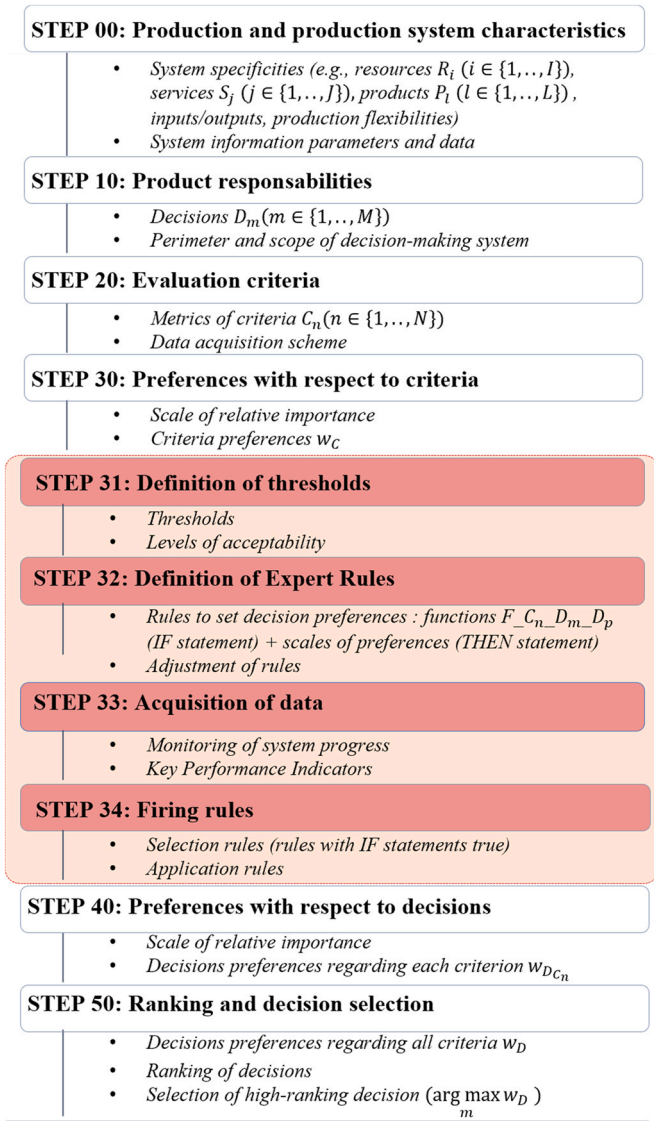


Fig. 3. Augmented AHP (A-AHP) adapted from the standard AHP.

3.5.2.3. *Products and associated control process.* A set of products of different types are considered. A manufacturing order (i.e., a ranked set of services to obtain, service by service) is associated with each product. When a product reaches a decisional node, it acquires manufacturing context indicators to analyze the situation and detect

potential anomalies. Based on this analysis, two operating modes are possible:

- In case no anomaly is detected, the product continues to operate in “normal” mode: each product follows a pre-established allocation planning (i.e., a ranked list of resources to visit for obtaining the set of services) elaborated by a centralized planning system.
- In case an anomaly is detected, the product relies on ontology automated reasoning to determine the type of disturbance. This aspect of ontology reasoning and inferencing to detect anomalies and determine disturbance types was investigated in a separate work (Bayar et al., 2016). The product then switches to a “disturbed” mode and must take control decisions to react to the disturbance.

3.5.3. STEP10 – product responsibilities

This step defines the decisional degrees of freedom allowed for SPs, i.e., decisions D_m ($m \in \{1, \dots, M\}$) that an SP can make, and its levels of responsibility/autonomy. This step sets the perimeter of product decision-making and defines the scope of human decision-maker/supervisor validation and/or intervention.

3.5.4. STEP20 – evaluation criteria

This step defines a set of criteria C_n ($n \in \{1, \dots, N\}$), metrics, and data acquisition schema with respect to which decisions are evaluated and ranked. For example, in a manufacturing context, metrics related to time, cost, and quality of service all need to be considered when making control decisions.

3.5.5. STEP30 – preferences with respect to criteria

This step defines a scale of relative importance (as the one shown in Table 1, taken from (Saaty, 1994), and establishes criteria preferences, regardless of decisions, based on a set of pairwise comparisons.

This pairwise comparison, carried out by a decision-maker, results in a square preference matrix $A = (a_{n,o})_{N \times N}$, where elements $a_{n,o}$ represent the scale of importance of a criterion C_n compared to criterion C_o . The matrix is characterized as described in (1):

$$\left\{ \begin{array}{l} a_{n,n} = 1, \quad \forall n \in \{1, \dots, N\} \\ a_{n,o} = \frac{1}{a_{o,n}}, \quad \forall n \in \{1, \dots, N\}, \quad \forall o \in \{1, \dots, N\}, \quad n \neq o \end{array} \right\} \quad (1)$$

The matrix A is then normalized to obtain matrix $A' = (a'_{n,o})_{N \times N}$ as shown in (2):

$$\left\{ a'_{n,o} = \frac{a_{n,o}}{\sum_n a_{n,o}}, \quad \forall n \in \{1, \dots, N\}, \quad \forall o \in \{1, \dots, N\} \right\} \quad (2)$$

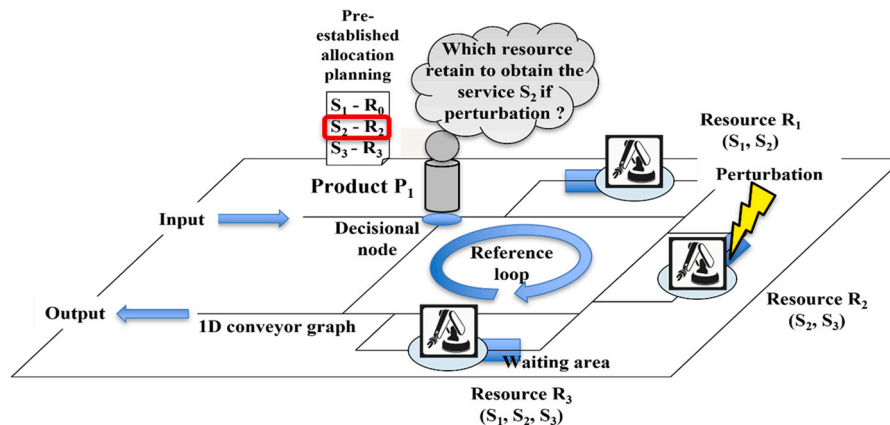


Fig. 4. Manufacturing system modeling.

Table 1

Scale of relative importance taken from (Saaty, 1994).

Scale	Numerical rating	Reciprocal
Equal importance	1	1
Equal to moderate importance	2	1/2
Moderate importance	3	1/3
Moderate to strong importance	4	1/4
Strong importance	5	1/5
Strong to very strong importance	6	1/6
Very strong importance	7	1/7
Very strong to the extreme importance	8	1/8
Extreme importance	9	1/9

Finally, the relative weight vector of criteria preferences, denoted $w_C = (w_{C_n})_{n \in \{1, \dots, N\}}$, is computed as shown in (3):

$$w_{C_n} = \frac{\sum_o a'_{n,o}}{N}, \quad \forall n \in \{1, \dots, N\} \quad (3)$$

A consistency test is carried out to check the values given in the comparison matrix (Saaty, 1994).

3.5.6. STEP31 – definition of thresholds

This step defines thresholds and levels of acceptability to provide intervals to better characterize elements of context that require decisions. These thresholds are used in the conditional part (IF statements) of the rules. Section 4.5 provides an example to better illustrate this.

3.5.7. STEP32 – definition of expert rules

This step defines the rules that will be used to dynamically update scales of preferences of control decisions during pairwise comparisons with respect to criteria (see Section 3.3 for more details).

3.5.8. STEP33 – acquisition of data

When a SP detects a disturbance (as explained in Section 3.2.2.3), it collects indicator values for each criterion. This data acquisition allows considering the evolution of system state and context dynamics.

3.5.9. STEP34 – firing rules

The rules, which IF statements are found true, are fired in order to adapt the scales of decision preferences with respect to criteria.

3.5.10. STEP40 – preferences with respect to decisions

This step performs a pairwise comparison of decisions regarding each criterion. Each pairwise comparison aims to set a preference for one decision over another with respect to a given criterion (e.g., using the preference scale of Table 1, decision D_m is X times more important than decision D_p with respect to a given criterion C_n). Considering a given criterion C_n , each pairwise comparison results in a square, M by M , preference matrix $B_{C_n} = (b_{m,p})_{C_n}, \forall (m, p) \in \{1, \dots, M\}$, and is characterized as in (4):

$$\left\{ \begin{array}{l} b_{m,m_{C_n}} = 1, \quad \forall m \in \{1, \dots, M\} \\ b_{m,p_{C_n}} = \frac{1}{b_{p,m_{C_n}}} \quad \forall m \in \{1, \dots, M\}, \quad \forall p \in \{1, \dots, M\}, \quad m \neq p \end{array} \right\} \quad (4)$$

For each criterion, the matrix B_{C_n} is then normalized as in (5):

$$\left\{ b'_{m,p_{C_n}} = \frac{b_{m,p_{C_n}}}{\sum_m b_{m,p_{C_n}}} \quad \forall m \in \{1, \dots, M\}, \quad \forall p \in \{1, \dots, M\} \right\} \quad (5)$$

The relative weight vector of decision preferences regarding each criterion C_n , denoted $w_{D_{C_n}} = (w_{D_{m_{C_n}}})_{m \in \{1, \dots, M\}}$ is computed as shown in (6):

$$w_{D_{m_{C_n}}} = \frac{\sum_p b'_{m,p_{C_n}}}{M}, \quad \forall m \in \{1, \dots, M\} \quad (6)$$

Finally, the weight vector w_D of decision preferences with respect to all criteria is computed as in (7):

$$w_D = \left(w_{D_m} \right)_{m \in \{1, \dots, M\}}, \quad \text{where } w_{D_m} = \sum_n w_{D_{m_{C_n}}} \times w_{C_n}, \quad \forall m \in \{1, \dots, M\} \quad (7)$$

3.5.11. STEP50 – ranking and decision selection

This step ranks a decision considering all criteria based on the weight vector of decision preferences w_D . The decision with the maximum value w_{D_m} is selected.

3.6. Dynamic adaptation of preferences based on expert rules

To overcome the limitations of the standard AHP procedure, Expert rules are introduced to adapt preferences dynamically to system state and disturbance context. The statements of rules can be abstracted according to the general statement shown in Fig. 5.

For a given context, evaluated by an $F_{C_n-D_m-D_p}$ function involving a set of indicators relative to the manufacturing system state and disturbance features, available decisions can be compared in pairs to determine preferences with respect to criterion C_n . The manufacturing system Expert should provide the expressions for context functions, and should provide a scale of the preference based on thresholds on criteria. An example is shown in Section 4.6 and in Appendices A2 to A4. The comparison functions are characterized as described in (8):

$$\left\{ \begin{array}{l} F_{C_n-D_m-D_m} = 1, \quad \forall m \in \{1, \dots, M\} \\ F_{C_n-D_m-D_p} = - F_{C_n-D_p-D_m}, \quad \forall n \in \{1, \dots, N\}, \\ \forall m \neq p \in \{1, \dots, M\} \end{array} \right\} \quad (8)$$

When a decision D_m is preferred to a decision D_p with respect to a criterion C_n , then the scale $b_{m,p_{C_n}}$ of the preference should be quantified, and the orientation of the preference should be shown using arrows, according to the notation shown in (9). This notation means that Decision D_m is preferred to Decision D_p with scale $b_{m,p_{C_n}}$ with respect to criterion C_n . The transpose notation is also set, according to the standard logic of pairwise comparison matrices.

$$D_m \xrightarrow{\text{Scale}} D_p \quad (9)$$

Consequently, the problem of making SPs learn how to make decisions resumes to the problem of setting arrows and scales between pairs of decisions, compared with respect to one criterion at a time, in order to consider a manufacturing system and disturbance context. This problem reformulation has the advantage to preserve the AHP ranking logic. The next section instantiates the Augmented AHP procedure on a case study.

4. Case study: the S.MART platform

The suggested approach is instantiated step by step on the S.MART platform, which is a flexible manufacturing system (FMS) serving research and educational purposes at *Université Polytechnique des Hauts-de-France* (Berdal et al., 2020; Trentesaux et al., 2013).

4.1. STEP00: product and production system characteristics

The S.MART platform, shown in Fig. 6, contains 6 workstations: a loading/unloading station (labelled R_1), 3 robotized stations involving STAUBLI robots (labelled R_2 , R_3 , and R_4), an automated inspection station (labelled R_5), and a rework station (labelled R_6) to deal

<p>For a given criterion $C_n, \forall n \in \{1, \dots, N\}$</p> <p>For any two available decisions, D_m and $D_p, \forall (m, p) \in \{1, \dots, M\}$</p> <p>Evaluate context $F_{C_n-D_m-D_p}$ function of manufacturing system context indicators and disturbance indicators</p> <p>IF</p> <p style="text-align: center;">$0 < F_{C_n-D_m-D_p} \leq \text{MinThreshold}_{C_n}$</p> <p>THEN update scale</p> <p style="text-align: center;">$D_m \xrightarrow{b_{m,p,C_n}} D_p$: Decision D_m is preferred to Decision D_p with scale b_{m,p,C_n} (moderate importance)</p> <p style="text-align: center;">$D_p \xrightarrow{1/b_{m,p,C_n}} D_m$: Decision D_p is preferred to Decision D_m with scale $1/b_{m,p,C_n}$</p> <p>IF</p> <p style="text-align: center;">$\text{MinThreshold}_{C_n} < F_{C_n-D_m-D_p} \leq \text{MaxThreshold}_{C_n}$</p> <p>THEN update scale</p> <p style="text-align: center;">$D_m \xrightarrow{b_{m,p,C_n}} D_p$: Decision D_m is preferred to Decision D_p with scale b_{m,p,C_n} (strong importance)</p> <p style="text-align: center;">$D_p \xrightarrow{1/b_{m,p,C_n}} D_m$: Decision D_p is preferred to Decision D_m with scale $1/b_{m,p,C_n}$</p> <p>IF</p> <p style="text-align: center;">$\text{MaxThreshold}_{C_n} < F_{C_n-D_m-D_p}$</p> <p>THEN update scale</p> <p style="text-align: center;">$D_m \xrightarrow{b_{m,p,C_n}} D_p$: Decision D_m is preferred to Decision D_p with scale b_{m,p,C_n} (very strong importance)</p> <p style="text-align: center;">$D_p \xrightarrow{1/b_{m,p,C_n}} D_m$: Decision D_p is preferred to Decision D_m with scale $1/b_{m,p,C_n}$</p>	Rule
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Fig. 5. Abstract statement of rules.

with product defects. Transportation and internal logistics are achieved using a monorail conveying system that enables flexible routing, with 10 shuttles. The transfer from one track to another is performed using switches. Decisional nodes (yellow nodes in Fig. 6) are located on some switches of the reference loop and allow making decisions to adapt the routing towards robotized stations. The decisional node located at the exit of the automated inspection station enables products to decide whether to be unloaded (no defects detected and no rework needed) or to go to the rework station in case of a quality defect.

The S.smart platform assembles 4 types of alphabetical letter-shaped products: "B", "E", "L", and "T". For this purpose, different services are provided to perform sub-assemblies of basic components on a plate as shown in Fig. 7: "Axis_comp", "L_comp", "L_comp", "r_comp", and "screw_comp".

Appendix A1 provides the ordered list of services to obtain, the pre-established allocation planning (i.e., the resource assigned to each service), as well as the time required to achieve each service. It also reports the alternative resource and service time that can be chosen for each service in case of disturbance.

4.2. STEP10: product responsibilities

In case of disturbance on a robotized station R_i ($i = 2, 3, 4$), a SP must choose one control decision among three available decisions:

- D_1 : Go to the assigned resource and wait in its queue until it is no longer busy.
- D_2 : Go to an alternative resource and wait in its queue until it is no longer busy.
- D_3 : Stay on the *reference loop* until at least one resource becomes available for the requested service.

With respect to the automated inspection and quality control station R_5 , if the product quality is found acceptable, then the product is directed towards the unloading station R_1 . Otherwise, in case some defects are detected, the product is directed towards the rework station R_6 to fix the defects, then it is directed towards the unloading station R_1 . Consequently, the suggested A-AHP mechanism is mainly deployed and used on the decisional nodes of the main reference loop.

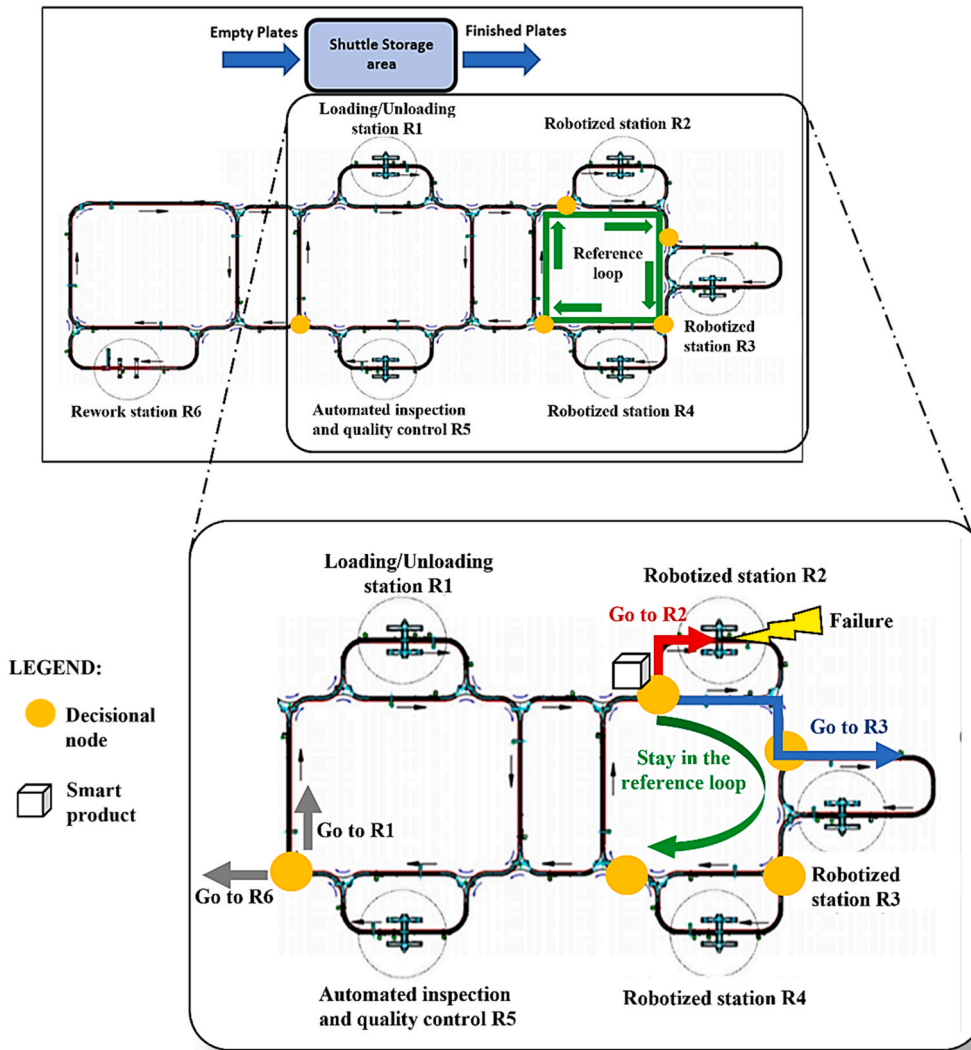


Fig. 6. Production system and product decisions.

4.3. STEP20: evaluation criteria

Indicators are defined to rank decisions with respect to Cost, Quality of Service (QoS), and Time criteria. As shown in Fig. 8, each decision is evaluated with respect to all indicators. Other criteria, such as environmental or sustainability criteria, are not considered in this paper but could be considered in future works.

4.3.1. Cost criteria C_1

This class includes metrics used to evaluate decisions according to economic concerns, and which are: PC_{R_i} , LC , $CSRL$. These indicators are explained in section 3.2.1 and are expressed in monetary units.

4.3.2. QoS criteria C_2

This class groups indicators that may influence the quality of service provided by resources (e.g., robots and their peripheral devices) to products. These indicators are related to the resource reliability and the performances of maintenance operations: TTF_{R_i} , TTR_{R_i} . These indicators are explained in section 3.2.1 and are expressed in time units. Also, these indicators are calculated based on analytics of the historical records of the robotized stations.

4.3.3. Time criteria C_3

This class includes metrics used to evaluate decisions according to flow time and which are: PT_{R_i} , WTQ_{R_i} , $WTRL$. These indicators are explained in section 3.2.1 and are expressed in time units.

4.4. STEP30: preferences with respect to criteria

Fig. 9 shows the pairwise comparisons between each couple of criteria using the scale of relative importance given in Table 1. For example, the scale of "5" appearing at the intersection of line 2 and column 1 in the matrix A of preferences between criteria as shown in Fig. 9, means that quality of service criteria C_2 are strongly preferred (strong importance) over cost criteria C_1 , whatever the decision is. The matrix A is then normalized, and the vector of criteria weights is computed as shown in Fig. 9.

To check the consistency of the values given in matrix A , a consistency ratio is calculated and shown in (10):

$$CR = 4.67\% \quad (10)$$

According to (Saaty, 1994), if the consistency ratio is less than 10 %, then the evaluations of criteria preferences can be deemed coherent.

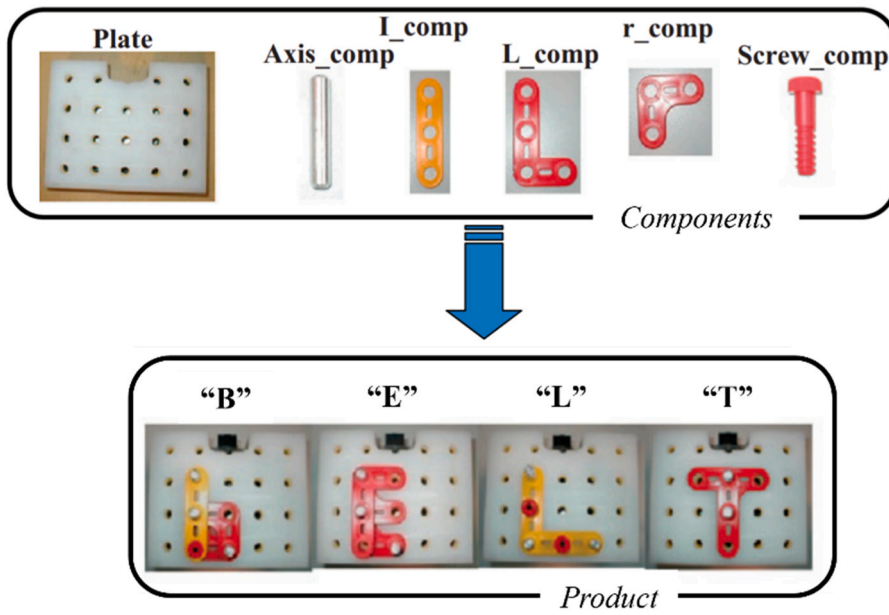


Fig. 7. Components and products.

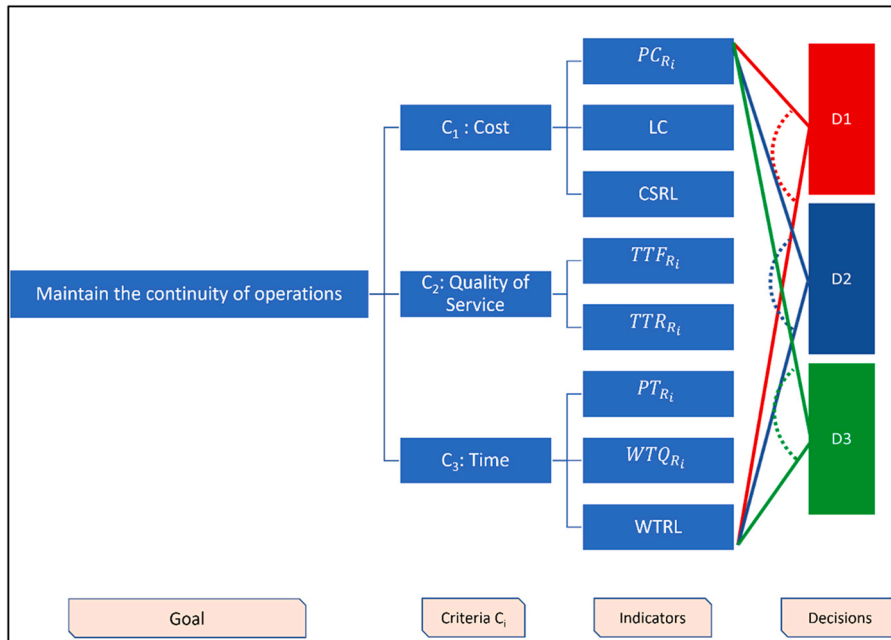


Fig. 8. AHP hierarchal decision framework.

$a_{n,o}$	C ₁	C ₂	C ₃
C ₁	1	0.2	0.14
C ₂	5	1	0.33
C ₃	7	3	1
Sum	13	4.2	1.47

$a'_{n,o}$	C ₁	C ₂	C ₃
C ₁	1/13	0.2/4.2	0.14/1.47
C ₂	5/13	1/4.2	0.33/1.47
C ₃	7/13	3/4.2	1/1.47

W_{C_n}	W_C
C ₁	0.07
C ₂	0.28
C ₃	0.64

Fig. 9. process of obtaining criteria weights.

Table 2

Thresholds to describe occurrences of disturbances.

Robotized station	$Thr_TTF_{R_i}$	$Thr_RPT_{R_i}$
R_2	500s	250s
R_3	500s	250s
R_4	500s	250s

Table 3

Thresholds on scales of relative importance.

Criteria	$MinThreshold_C_n$	$MaxThreshold_C_n$
C_1	0.5\$	2.5\$
C_2	1000s	10000s
C_3	60s	500s

4.5. STEP31: define thresholds

Manufacturing system Experts provide thresholds to describe intervals and levels of acceptability to characterize elements of context that require decisions. Three types of thresholds are defined as follows:

- $Thr_RPT_{R_i}$: are thresholds on the required time (RPT_{R_i}) to achieve a service on a robotized station R_i ($i = 2, 3, 4$) (see Table 2). Whenever this threshold is exceeded, a disturbance is likely to be occurring. The required time to achieve a service on a robotized station is expressed as in (11):

$$RPT_{R_i} = PT_{R_i} + TTR_{R_i} + WTQ_{R_i}, i = 2, 3, 4 \quad (11)$$

- $Thr_TTF_{R_i}$: is a threshold on the time to failure of robotized station R_i ($i = 2, 3, 4$) (see Table 2). Such thresholds can be used to consider the causal relation between resource reliability and the quality of service.
- Thresholds on scales of relative importance (see Table 3) provide upper and lower bounds on evaluations of manufacturing system context when making pairwise comparisons between any two decisions with respect to a class of criteria. The lower bound is referred to as " $MinThreshold_C_n$ ", whereas the upper bound is referred to as " $MaxThreshold_C_n$ ". These thresholds are used in the definition of Expert rules (see Section 3.3), and will be illustrated with an example in Section 4.6.

4.6. STEP32: define expert rules

Rules are defined for each criterion based on the design pattern explained in Fig. 5. Appendices A2 to A4 provide the set of all Expert rules regarding Time, Cost and Quality criteria for this case study. The details of the expressions of context functions $F_{C_n_D_m_D_p}$ as well as the adapted scales of preferences of decisions with respect to each criterion C_n are also provided.

For example, let us consider a context function " $F_{C_3_D_1_D_2}$ " related to the Time criterion C_3 . $F_{C_3_D_1_D_2}$ compares the required processing times of available resources (suggested by the decisions

Table 4

Example of Expert rule.

RuleId	IF Condition	THEN Statement
$R_{C_3_2}$	$MinThreshold_C_3, < F_{C_3_D_1_D_2} < MaxThreshold_C_3$	$D_1 \xrightarrow{5} D_2 \quad D_2 \xrightarrow{\frac{1}{5}} D_1$

Table 5

Example of a set of collected indicators.

Cost: criterion C_1			
Resources	PC_{R_i}	LC	$CSRL$
R_2	1\$	0\$	2\$
R_3	1.2\$	1.5\$	
Quality of Service: criterion C_2			
Resources	TTF_{R_i}	TTR_{R_i}	
R_2	24338s	336.24s	
R_3	28800s	0s	
Time: criterion C_3			
Resources	PT_{R_i}	WTQ_{R_i}	$WTRL$
R_2	5s	0s	50s
R_3	5s	0s	

to be compared, namely D_1 and D_2 in this example) with respect to the defined time thresholds according to the formula given in (12).

$$F_{C_3_D_1_D_2} = RPT_{Resource\ of\ D_2} - RPT_{Resource\ of\ D_1} \quad (12)$$

As shown in Table 4, a preference of D_1 compared to D_2 is given a scale of 5 if the evaluation of $F_{C_3_D_1_D_2}$ is found within the interval [$MinThreshold_C_3$, $MaxThreshold_C_3$].

At this point in the presentation of the case study, the two first steps in the suggested supervised learning approach described in Section 3.1 are finished. The set of experimentation scenarios provided by the decision maker will be described in Section 5. Meanwhile, to continue with tracing the execution of the suggested control mechanism, step 3 in the suggested supervised learning approach (see Section 3.1) is described next, in which simulation is started and products are active to make decisions.

4.7. STEP33: data acquisition

To illustrate product-embedded decision-making, let us consider as an example a "B"-shaped product, which is first loaded through station R_1 , then has to go to R_2 for axis mounting, according to its pre-established allocation planning shown in Appendix A1. At the decisional node located before R_2 shown in Fig. 6, the product collects indicators on the status of the manufacturing system to detect disturbances and to initiate decision-making. An example of such collected indicators is shown in Table 5.

4.8. STEP34: rule firing

For the considered example of the "B"-shaped product, let us assume that a failure on R_2 (the product default allocated resource) is detected. Next, the product has to evaluate context functions $F_{C_n_D_m_D_p}$, and to compare the outcomes of the evaluations to the thresholds on scales of relative importance introduced in Section 4.5. Those rules which "IF statements" evaluate to true are fired, and their "THEN statements" are applied to update decision preferences with respect to each criterion. For example, Fig. 10 shows three rules for the Time criterion C_3 , which "IF statements" evaluate to true based on the data acquired in Table 5. Accordingly, pairwise comparisons between decisions regarding the Time criterion C_3 are performed, and Matrix $B_{C_n=3}$ is obtained.

The same process shown in Fig. 10 is applied to fire rules and update decision preferences with respect to the other criteria C_1 and C_2 .

RuleId	IF statement	THEN statement
R_C3_5	$MinThreshold_{C_3} = 60 <$ $F_{C_3-D_2-D_1}$ $= -F_{C_3-D_1-D_2}$ $= -(RPT_{R\ of\ D_2 \rightarrow R_3} - RPT_{R\ of\ D_1 \rightarrow R_2})$ $= -((5 + 0 + 0) - (5 + 336.24 + 0))$ $= 336.24$ $< MaxThreshold_{C_3} = 500$	$D_2 \xrightarrow{5} D_1$ $D_1 \xrightarrow{\frac{1}{5}} D_2$
R_C3_11	$MinThreshold_{C_3} = 60 <$ $F_{C_3-D_3-D_1}$ $= -F_{C_3-D_1-D_3}$ $= -(WTRL - RPT_{R\ of\ D_1 \rightarrow R_2})$ $= -(50 - (5 + 336.24 + 0))$ $= 291.24$ $< MaxThreshold_{C_3} = 500$	$D_3 \xrightarrow{5} D_1$ $D_1 \xrightarrow{\frac{1}{5}} D_3$
R_C3_13	$F_{C_3-D_2-D_3} = WTRL$ $- RPT_{R\ of\ D_2 \rightarrow R_3})$ $= 50 - (5 + 0 + 0)$ $= 45$ $< MinThreshold_{C_3} = 60$	$D_2 \xrightarrow{3} D_3$ $D_3 \xrightarrow{\frac{1}{3}} D_2$

Matrix $B_{C_n=3}$

	$b_{m,p_{C_n}}$	D_1	D_2	D_3
C_3	D_1	1	0.2	0.2
	D_2	5	1	3
	D_3	5	0.33	1

Fig. 10. Example of rule activation and pairwise comparison of decisions according to Time criterion.

4.9. STEP40: preferences with respect to decisions

The obtained results, shown in Fig. 11, correspond to the vectors $w_{D_{mC_n}}$ of weights of decision preferences with respect to each criterion C_n .

4.10. STEP50: ranking and decision selection

Finally, the matrix of weights of decisions is multiplied by the vector of weights of criteria to obtain the ranking of decisions considering all criteria. In the example under study; the product chooses the decision with the maximum value in the vector of weights of decisions w_D , and which is D_2 : Go to the alternative resource (see Fig. 12).

The next part relates the performed experimentations and analyzes the obtained results.

5. Experimentation and results

In order to assess its performance, the A-AHP is implemented on AnyLogic 8.7.10 University Edition using a multi-agent system simulation of the S.MART platform described previously.

5.1. Multi-agent system description

Product agents interact with resource agents to get their status and local performance indicators. A system agent provides indicators on overall system performance, and allows interfacing enterprise

	Matrix $B = (b_{m,p})_{C_n}$ of preferences between decision for each criterion	Normalized Matrix $B' = (b'_{m,p})_{C_n}$	Vector $w_{D_{C_n}}$ of decision weights for each criterion																																								
Cost criterion C_1	<table border="1"> <thead> <tr> <th>$b_{m,p_{C_1}}$</th> <th>D_1</th> <th>D_2</th> <th>D_3</th> </tr> </thead> <tbody> <tr> <th>D_1</th> <td>1</td> <td>5</td> <td>5</td> </tr> <tr> <th>D_2</th> <td>0,20</td> <td>1</td> <td>5</td> </tr> <tr> <th>D_3</th> <td>0,20</td> <td>0,20</td> <td>1</td> </tr> </tbody> </table>	$b_{m,p_{C_1}}$	D_1	D_2	D_3	D_1	1	5	5	D_2	0,20	1	5	D_3	0,20	0,20	1	<table border="1"> <thead> <tr> <th>$b'_{m,p_{C_1}}$</th> <th>D_1</th> <th>D_2</th> <th>D_3</th> </tr> </thead> <tbody> <tr> <th>D_1</th> <td>0,75</td> <td>0,81</td> <td>0,45</td> </tr> <tr> <th>D_2</th> <td>0,15</td> <td>0,16</td> <td>0,45</td> </tr> <tr> <th>D_3</th> <td>0,10</td> <td>0,03</td> <td>0,09</td> </tr> </tbody> </table>	$b'_{m,p_{C_1}}$	D_1	D_2	D_3	D_1	0,75	0,81	0,45	D_2	0,15	0,16	0,45	D_3	0,10	0,03	0,09	<table border="1"> <thead> <tr> <th>$w_{D_{C_1}}$</th> <th>$w_{D_{C_1}}$</th> </tr> </thead> <tbody> <tr> <th>D_1</th> <td>0,67</td> </tr> <tr> <th>D_2</th> <td>0,26</td> </tr> <tr> <th>D_3</th> <td>0,08</td> </tr> </tbody> </table>	$w_{D_{C_1}}$	$w_{D_{C_1}}$	D_1	0,67	D_2	0,26	D_3	0,08
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D_3	5	0,33	1																																								
$b'_{m,p_{C_3}}$	D_1	D_2	D_3																																								
D_1	0,09	0,13	0,05																																								
D_2	0,45	0,65	0,71																																								
D_3	0,45	0,22	0,24																																								
$w_{D_{C_3}}$	$w_{D_{C_3}}$																																										
D_1	0,09																																										
D_2	0,60																																										
D_3	0,30																																										

Fig. 11. Pairwise comparisons of decisions, for each criterion.

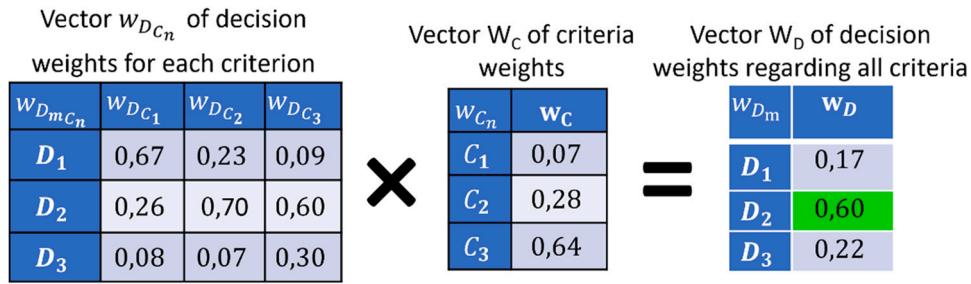


Fig. 12. Decisions' relative weights with respect to all criteria.

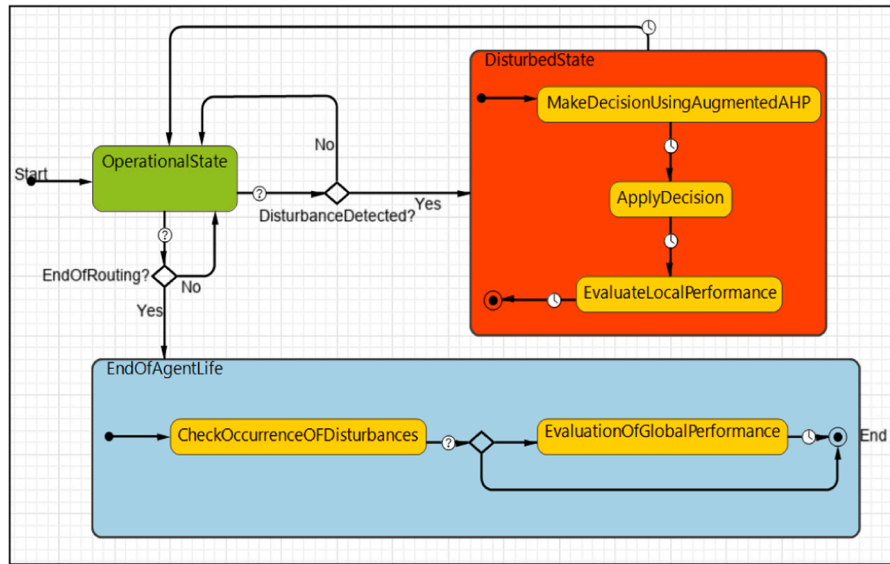


Fig. 13. AnyLogic Finite State Machine of product agents.

information systems and manufacturing Experts (Attajer et al., 2021). The product and resource agents are described in the following sections.

5.1.1. Product agents

Fig. 13 provides an AnyLogic Finite State Machine representation of the behavior of a product agent.

When a product is released into the simulation model of the platform (according to an arrival distribution that will be described in Section 5.2), a product agent is associated and enters an "operational state", where it requests the system agent to acquire the pre-established allocation planning from Enterprise Information Systems. In the operational state, the product agent monitors the progress of the realization of the services, as well as the occurrence of disturbances. If no disturbance is detected, the product agent follows the pre-established planning step by step until all services are obtained. If a disturbance is detected, the product agent enters a "disturbed state", in which it applies A-AHP to react to the disturbance. As soon as a decision is selected, it is applied. Local performance is then evaluated and stored. The product agent then resumes back to the operational state to continue the realization of the remaining services in its pre-established allocation planning. When all services are realized, and in case disturbances occurred, the set of indicators related to the performance of the product, as well as global manufacturing system performance indicators are evaluated and stored to enable analytics about the reaction to disturbances.

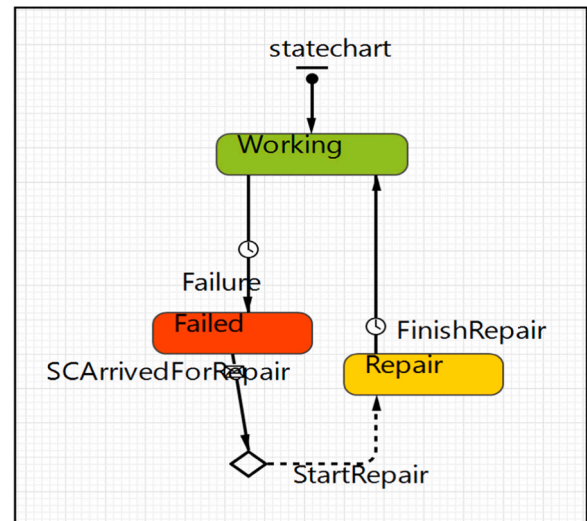


Fig. 14. AnyLogic Finite State Machine of robotized station agents.

Table 6
Criteria pairwise comparison and weights of the standard AHP.

Pairwise comparison matrix				Consistency ratio	Criteria weights
Cost	Quality	Time	4 %		
Cost	1	0,33	0,20		0,11
Quality	3	1	0,33		0,26
Time	5	3	1		0,63

Table 7
Global parameters for considered scenarios.

Product type "B" arrival rate (per hour)	Product type "E" arrival rate (per hour)	Product type "L" arrival rate (per hour)	Product type "T" arrival rate (per hour)
10/h	10/h	10/h	10/h

Table 8
Model parameters of considered scenarios.

	Failure rates (FR_{R_i}) of Robotized resources (per day)	Mean time to repair (MTTR) of Robotized resources (seconds)
Scenario (E#1,1)	$FR_{R_2} = 1/d$ $FR_{R_3} = 1/d$ $FR_{R_4} = 1/d$	180 s
Scenario (E#1,2)	$FR_{R_2} = 7/d$ $FR_{R_3} = 1/d$ $FR_{R_4} = 1/d$	180 s
Scenario (E#1,3)	$FR_{R_2} = 7/d$ $FR_{R_3} = 7/d$ $FR_{R_4} = 7/d$	180 s

5.1.2. Resource agents

A resource agent is associated with each resource. Fig. 14 provides an AnyLogic Finite State Machine representation of the behavior of agents associated with robotized stations.

A robotized station can be in working state, in failure (meaning that it is waiting for corrective maintenance), or under repair.

5.2. Experimental protocol

Objectives: three sets of experiments, referred as Experiment #1, #2 and #3, highlight the advantages of the A-AHP strategy compared to two other control strategies:

- Inflexible Strategy (IS), in which each product follows its pre-established allocation planning even in case of disturbances. The product does not take advantage of system flexibility. Instead, it waits in the queue of the resource providing the next service until the resource becomes available. The comparison to such a strategy is interesting because it shows the consequences of disturbances in case of no reaction decision is made.
- Standard AHP (Std-AHP) as described before. The pairwise comparison of the criteria and their weights are reported in Table 6.

Inputs: To stress the benefits and limits of each strategy, the variation of the following input parameters are considered for each experiment:

- The disturbances affecting the robotized resources, defined through the failure rates and the times to repair (i.e. the failure duration).
- The product arrival rates.

Outputs: five performance indicators are considered in the experimentations:

- Avg_TT: average throughput time (in seconds), which corresponds to the average time taken to realize all services required by products.
- Avg_Cost: average production cost in monetary units to manufacture a product.
- Avg_TP: average throughput of products, which corresponds to the average number of products manufactured per hour.
- Avg_WT_R: average waiting time for products in the queue of resources (in seconds).
- Avg_WT_Loop: average waiting time for products in the reference loop (in seconds).

General considerations: The experimentations consider a one-month simulation and 100 replications for each scenario. Products are released according to an arrival exponential distribution with an arrival rate (number of products per hour). The failure function of robotized stations is an exponential distribution with the parameter failure rate FR_{R_i} (number of failures per day). The time to repair follows a triangular distribution.

5.3. Experimentation and results

The following sections relate the different experimentations and the obtained results.

5.3.1. Experiment #1: impact study of the failure rate of the robotized stations

For this experiment, the fixed parameters are presented in Table 7.

Three scenarios as summarized in Table 8. In these scenarios, the mean time to repair is fixed and only the failure rate of robotized resources is varied as follow:

- Scenario (E#1,1): all robotized resources have a low failure rate.

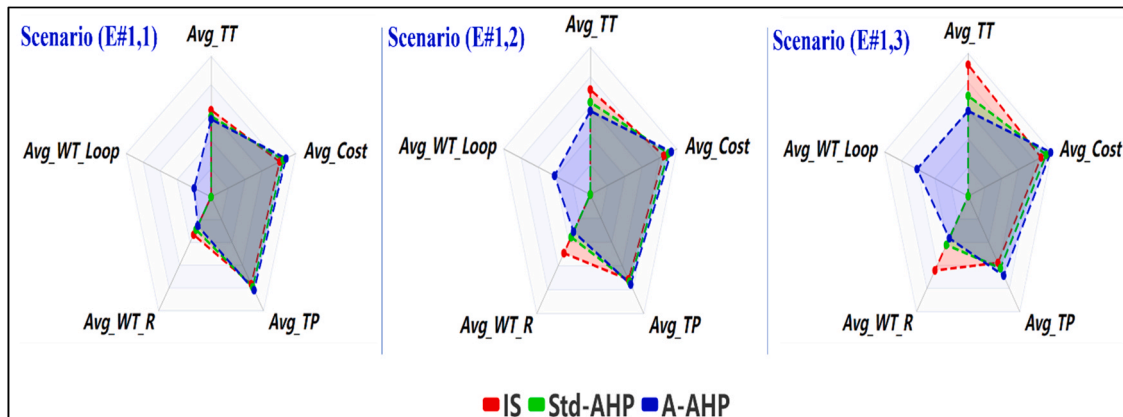


Fig. 15. Results of simulation for Experiment#1.

Table 9
Average of KPIs compared to IS in % for Experiment#1.

Scenario	KPI	Std-AHP	A-AHP
Scenario (E#1,1)	Reduction of Avg_TT compared to IS	4,09 %	5,15 %
	Reduction of Avg_Cost compared to IS	-5,19 %	-9,09 %
	Reduction of Avg_TP compared to IS	-0,55 %	-1,10 %
	Reduction of Avg_WT_R compared to IS	13,50 %	23,62 %
	Reduction of Avg_WT_Loop compared to IS	-	-
Scenario (E#1,2)	Reduction of Avg_TT compared to IS	11,99 %	20,33 %
	Reduction of Avg_Cost compared to IS	-6,17 %	-9,88 %
	Reduction of Avg_TP compared to IS	-2,74 %	-5,85 %
	Reduction of Avg_WT_R compared to IS	27,33 %	36,44 %
	Reduction of Avg_WT_Loop compared to IS	-	-
Scenario (E#1,3)	Reduction of Avg_TT compared to IS	23,70 %	35,17 %
	Reduction of Avg_Cost compared to IS	-7,23 %	-13,25 %
	Reduction of Avg_TP compared to IS	-8,00 %	-19,15 %
	Reduction of Avg_WT_R compared to IS	34,39 %	43,26 %
	Reduction of Avg_WT_Loop compared to IS	-	-

Table 10
Model parameters of considered scenarios.

	Failure rate (FR) of Robotized resources (per day)	Mean time to repair ($MTTR_{R_i}$) of Robotized resources (seconds)
Scenario (E#2,1)	2/d	$MTTR_{R_2} = 90s$ $MTTR_{R_3} = 90s$ $MTTR_{R_4} = 90s$
Scenario (E#2,2)	2/d	$MTTR_{R_2} = 600s$ $MTTR_{R_3} = 90s$ $MTTR_{R_4} = 90s$
Scenario (E#2,3)	2/d	$MTTR_{R_2} = 600s$ $MTTR_{R_3} = 600s$ $MTTR_{R_4} = 600s$

- Scenario (E#1,2): The resource R_2 has a high failure rate, This resource is chosen because it is the most used and so represents a critical resource (see the pre-established allocation planning Appendix A1).
- Scenario (E#1,3): all robotized resources have a high failure rate.

As for the impact of failure rate on the system's performance, Fig. 15 and Table 9 show the following results:

- Avg_TT, Avg_TP, and Avg_WT_R values are highly sensible to failure rate for all strategies under study as the unavailability of resources increases. Accordingly, with a high failure rate,

congestion in conveyors and queues, long lead times and low throughput are observed.

- In the first scenario (E#1,1) with low failure rates for all robotized resources, A-AHP outperforms the other control strategies regarding Avg_TT, Avg_TP and Avg_WT_R. On the other hand, the Avg_Cost value is higher as there are additional logistical costs to be considered. Also, Avg_WT_Loop for IS and Std-AHP are null because products do not go and stay in the *reference loop*. However, the Avg_WT_Loop value for A-AHP is not null since products can stay in the *reference loop* instead of waiting in the queue of resources.
- In the second scenario (E#1,2), in which the failure rate of the most used resource R_2 is high, a drop in the performance of the system for all applied control strategies is observed. However, A-AHP always outperforms the other strategies regarding all KPIs except Avg_Cost and Avg_WT_Loop.
- In the third scenario (E#1,3), in which all robotized resources have a high failure rate, the system's performance drops considerably. All KPIs values are downgraded. However, A-AHP's KPIs degradation is not as drastic as the degradation of performance in other strategies, given its dynamic characteristics that take full advantage of the flexibility of the system.

5.3.2. Experiment #2: impact study of the time to repair of the robotized resources

As for the previous experiment, the fixed parameters are described in Table 6.

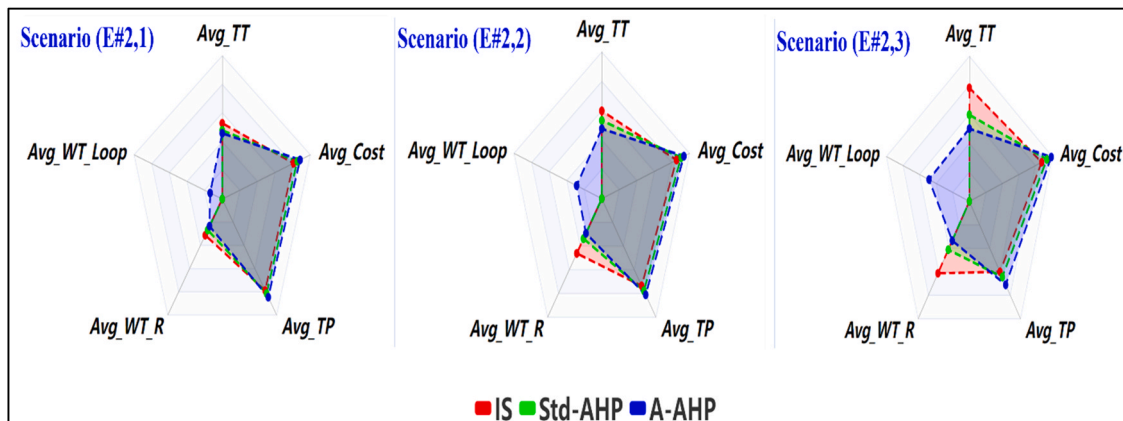


Fig. 16. Results of simulation for Experiment#2.

Table 11
Average of KPIs compared to IS in % for Experiment#2.

Scenario	KPI	Std-AHP	A-AHP
Scenario (E#1,1)	Reduction of Avg_TT compared to IS	5,22 %	6,26 %
	Reduction of Avg_Cost compared to IS	-5,19 %	-9,09 %
	Reduction of Avg_TP compared to IS	-0,53 %	-1,60 %
	Reduction of Avg_WT_R compared to IS	14,38 %	25,16 %
	Reduction of Avg_WT_Loop compared to IS	-	-
Scenario (E#1,2)	Reduction of Avg_TT compared to IS	10,95 %	20,33 %
	Reduction of Avg_Cost compared to IS	-6,17 %	-9,88 %
	Reduction of Avg_TP compared to IS	-5,68 %	-10,21 %
	Reduction of Avg_WT_R compared to IS	26,93 %	36,64 %
	Reduction of Avg_WT_Loop compared to IS	-	-
Scenario (E#1,3)	Reduction of Avg_TT compared to IS	23,70 %	35,93 %
	Reduction of Avg_Cost compared to IS	-7,23 %	-13,25 %
	Reduction of Avg_TP compared to IS	-7,34 %	-18,44 %
	Reduction of Avg_WT_R compared to IS	32,78 %	45,42 %
	Reduction of Avg_WT_Loop compared to IS	-	-

Table 12
Global parameters for considered scenarios.

Failure rate (FR) of Robotized resources (per day)	Mean time to repair (MTTR) of Robotized resources (seconds)
2/d	180 s

Three scenarios are reported in Table 10. In these scenarios, the failure rate is fixed and the mean time to repair of robotized resources is varied as follow:

- Scenario (E#2,1): all robotized resources have a low mean time to repair.
- Scenario (E#2,2): the resource R_2 has a high mean time to repair.
- Scenario (E#2,3): all robotized resources have a high mean time to repair.

As for the impact of mean time to repair on the system's performance, Fig. 16 and Table 11 show the following results:

- Avg_TT, Avg_TP, and Avg_WT_R values are highly sensitive to mean time to repair value for IS, as products stack in the queue waiting for their assigned resource to be repaired. In contrast, for Std-AHP and A-AHP, the degradation of these KPIs is less noticeable, since they take advantage of the flexibility of the system.
- It can be concluded that in the case of lower frequency and higher duration of disturbances, A-AHP outperforms the other strategies, as it takes fully advantage of system's flexibility.

5.3.3. Experiment #3: impact study of the products arrival rate

For this experiment, the fixed parameters are presented in Table 12.

Three scenarios are reported in Table 13. The resources failure rates and mean time to repair are fixed. In these scenarios, the arrival rate of each product type is varied as follow:

- Scenario (E#3,1): all product types have a low arrival rate.
- Scenario (E#3,2): quantity mix-on-demand is considered: low arrival rate for product type "B", medium arrival rate for product type "E" and "L", and high arrival for product type "T".
- Scenario (E#3,3): all product types have a high arrival rate.

Table 13
Model parameters of considered scenarios.

	Product type "B" arrival rate (per hour)	Product type "E" arrival rate (per hour)	Product type "L" arrival rate (per hour)	Product type "T" arrival rate (per hour)
Scenario (E#3,1)	5/h	5/h	5/h	5/h
Scenario (E#3,2)	5/h	10/h	10/h	20/h
Scenario (E#3,3)	20/h	20/h	20/h	20/h

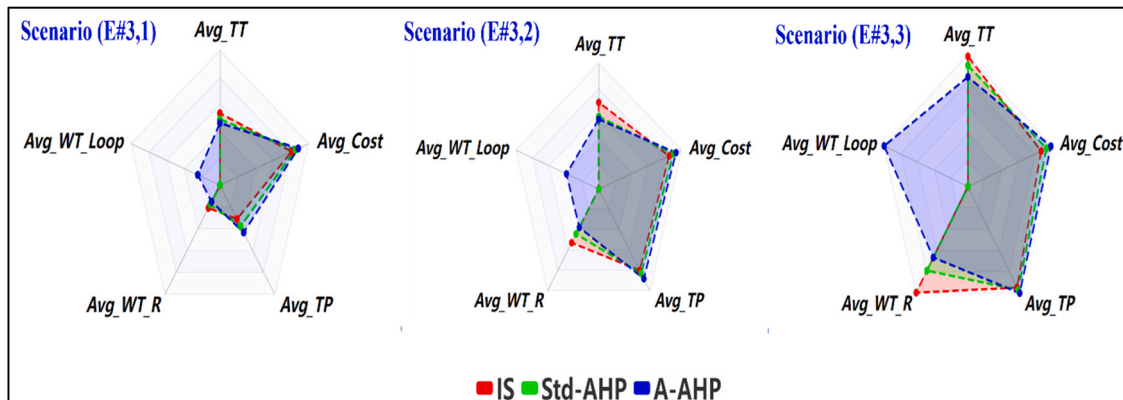


Fig. 17. Results of simulation for Experiment#3.

Table 14
Average of KPIs compared to IS in % for Experiment#3.

Scenario	KPI	Std-AHP	A-AHP
Scenario (E#1,1)	Reduction of Avg_TT compared to IS	3,12 %	5,52 %
	Reduction of Avg_Cost compared to IS	-5,15 %	-9,01 %
	Reduction of Avg_TP compared to IS	-0,59 %	-1,71 %
	Reduction of Avg_WT_R compared to IS	14,51 %	26,08 %
	Reduction of Avg_WT_Loop compared to IS	-	-
Scenario (E#1,2)	Reduction of Avg_TT compared to IS	16,31 %	19,47 %
	Reduction of Avg_Cost compared to IS	-6,17 %	-9,88 %
	Reduction of Avg_TP compared to IS	-3,56 %	-10,21 %
	Reduction of Avg_WT_R compared to IS	16,18 %	28,46 %
	Reduction of Avg_WT_Loop compared to IS	-	-
Scenario (E#1,3)	Reduction of Avg_TT compared to IS	6,90 %	15,81 %
	Reduction of Avg_Cost compared to IS	-7,23 %	-13,25 %
	Reduction of Avg_TP compared to IS	-2,29 %	-5,43 %
	Reduction of Avg_WT_R compared to IS	20,77 %	33,08 %
	Reduction of Avg_WT_Loop compared to IS	-	-

As for the impact of arrival rate of product on the system's performance, Fig. 17 and Table 14 show the following results:

- In scenarios (E#3,1) and (E#3,2); with lower arrival rate and medium mix-on-demand quantity respectively, A-AHP outperforms the other strategies as it takes full advantage of system's flexibility.
- However, it becomes less competitive with a higher arrival rate in scenario (E#3,1), because a large number of products requiring different services and thus all the resources of the system are solicited. Accordingly, conveyors and queues become more congested with long lead times and throughput of the system.

6. Conclusion and future research

The main contribution of this article is to promote activeness of Smart Products (SPs) with respect to decision-making and control processes to react to disturbances at operational stage. This is achieved through a hierarchical framework, where manufacturing system Experts delegate dispatching control responsibilities to SPs through the definition of rules, which are then used by SPs to adapt preferences among dispatching control decisions. Once preferences are adapted, SPs rely on an Augmented Analytic Hierarchy Process (A-AHP) to select the next resource that will provide the next required service by selecting a control decision from a set of available control decisions. Through A-AHP, SPs are enabled to select the next resource that will deliver the next required service, unlike the philosophy of dispatching rules, where products are usually passive and undergo dispatching decisions, made by smart resources or other scheduling systems. Expert rules offer an explicit way to provide knowledge about scales and preferences between control decisions with respect to specific disturbed contexts and feedback on performance. The so Augmented AHP (AHP) offers a white-box, explicit mechanism that enables explaining the decisions made by SPs. To validate performance, the suggested approach is implemented using a multi-agent discrete event simulation of a real assembly CPMS. Experimentations and results highlight that A-AHP outperforms the standard AHP and inflexible strategies as it takes full advantage of the CPMS flexibility. However, it becomes less competitive with a higher frequency of disturbances and higher arrival rate of products.

The contributions of this work can be discussed and extended in many ways. Three categories of improvements can be considered. The first category is related to optimization, flexibility and reactivity. Being based on distributed control, the main goal of the suggested approach is to take full advantage of CPMS flexibility in order to improve reactivity and responsiveness to disturbances and risks through decentralization of dispatching control decisions on SPs. More investigation is required to quantify the performance of the

suggested approach with respect to global versus local optimization. It is worth noticing that the suggested architecture shown in Fig. 2 enables such investigation through data analytics. As SPs make decisions to react to disturbances, it is possible to capitalize on this knowledge within a Case-Based Reasoning architecture. Similarity reasoning can be used to improve thresholds, rules and decision-making processes, both off-line (through comparison to scheduling optimization algorithms), and on-line (through using CBR to react to similar occurrences of disturbances using optimized reference schedules and reaction strategies).

The second category is related to AHP core processes. For example, the hierarchical A-AHP decision framework can be enriched with more criteria and indicators, particularly related to sustainability and energy efficiency. Also, group decision-making mechanisms can be considered to aggregate the opinions and preferences of several Experts, thus alleviating the subjectivity of the set-ups provided by only one Expert. Fuzzy logic can be used as an alternative representation of numerical values of thresholds to consider uncertainties, ambiguities, and different appreciations of numerical values, especially when many Experts are involved. These enrichments can easily be integrated, without questioning the downstream decision mechanisms, which shows one kind of genericity of the suggested approach.

The third category is related to the adaptability, scalability and evolution of decision mechanisms with respect to the evolution of the characteristics of the manufacturing system. For example, Ripple Down Rules (RDR) mechanisms can be considered to improve the rule-based adaptation of preferences (Compton and Kang, 2021). The above mentioned CBR framework would enable an automatic generation of rules from the captured knowledge, and therefore bring additional support to manufacturing system experts in defining and refining rules, while preserving their position at the heart of the decision-making loop and control processes. Finally, Reinforcement Learning can be considered to automate and fine tune the scaling of preferences between decisions.

Credit authorship contribution statement

The authors declare no conflict of interests.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A1. Pre-established routings and allocation of the services on resources

"B" product			"E" product			"L" product			"T" product		
Service	Ass. Res. (ST)	Alt. Res. (ST)	Service	Ass. Res. (ST)	Alt. Res. (ST)	Service	Ass. Res. (ST)	Alt. Res. (ST)	Service	Ass. Res. (ST)	Alt. Res. (ST)
1 Loading	R ₁ (15)	–	Loading	R ₁ (15)	–	Loading	R ₁ (15)	–	Loading	R ₁ (15)	–
2 Axis mounting	R ₂ (5)	R ₃ (5)	Axis mounting	R ₂ (5)	R ₃ (5)	Axis mounting	R ₂ (5)	R ₃ (5)	Axis mounting	R ₂ (5)	R ₃ (5)
3 r_comp mounting	R ₃ (5)	R ₂ (5)	r_comp mounting	R ₃ (5)	R ₂ (5)	L_comp mounting	R ₄ (5)	R ₂ (5)	r_comp mounting	R ₃ (5)	R ₂ (5)
4 L_comp mounting	R ₄ (5)	R ₂ (5)	L_comp mounting	R ₄ (5)	R ₂ (5)	Screw_comp mounting	R ₂ (5)	R ₄ (5)	L_comp mounting	R ₄ (5)	R ₂ (5)
5 Screw_comp mounting	R ₂ (5)	R ₄ (5)	Inspection	R ₅ (20)	–	Inspection	R ₅ (20)	–	Inspection	R ₅ (20)	–
6 Inspection	R ₅ (20)	–	Unloading	R ₁ (15)	–	Unloading	R ₁ (15)	–	Unloading	R ₁ (15)	–
7 Unloading	R ₁ (15)	–									

Legend:

Ass. Res. (ST): Assigned resource and Service Time (ST) in seconds

Alt. Res. (ST): Alternative resources and Service Time (ST) in seconds

Appendix A2. Set of expert rules regarding cost criterion C₁

	Decision D ₁			Decision D ₂			Decision D ₃		
	RuleId	Condition	Statement	RuleId	Condition	Statement	RuleId	Condition	Statement
Decision D ₁		1		R _{C₁-1}	$0 < (F_{C_1,D_1,D_2} = LC + PC_{R_{of D_2}} - PC_{R_{of D_1}}) \leq MinThreshold_{C_1}$	$D_1 \xrightarrow{\frac{2}{3}} D_2$ $D_2 \xrightarrow{\frac{1}{3}} D_1$	R _{C₁-7}	$0 < (F_{C_1,D_1,D_3} = CSRL - PC_{R_{of D_1}}) \leq MinThreshold_{C_1}$	$D_1 \xrightarrow{\frac{3}{5}} D_3$ $D_3 \xrightarrow{\frac{1}{5}} D_1$
			R _{C₁-2}	$MinThreshold_{C_1} < F_{C_1,D_1,D_2} \leq MaxThreshold_{C_1}$	$D_1 \xrightarrow{\frac{4}{5}} D_2$ $D_2 \xrightarrow{\frac{1}{5}} D_1$	R _{C₁-8}	$MinThreshold_{C_1} < F_{C_1,D_1,D_3} \leq MaxThreshold_{C_1}$	$D_1 \xrightarrow{\frac{5}{8}} D_3$ $D_3 \xrightarrow{\frac{1}{8}} D_1$	
			R _{C₁-3}	$MaxThreshold_{C_1} < F_{C_1,D_1,D_2}$	$D_1 \xrightarrow{\frac{2}{3}} D_2$ $D_2 \xrightarrow{\frac{2}{3}} D_1$	R _{C₁-9}	$MaxThreshold_{C_1} < F_{C_1,D_1,D_3}$	$D_1 \xrightarrow{\frac{2}{3}} D_3$ $D_3 \xrightarrow{\frac{1}{3}} D_1$	
Decision D ₂	R _{C₁-4}	$0 < (F_{C_1,D_2,D_1} = -F_{C_1,D_1,D_2}) \leq MinThreshold_{C_1}$	$D_2 \xrightarrow{\frac{3}{4}} D_1$ $D_1 \xrightarrow{\frac{1}{4}} D_2$				R _{C₁-13}	$0 < (F_{C_1,D_2,D_3} = CSRL - PC_{R_{of D_2}}) \leq MinThreshold_{C_1}$	$D_2 \xrightarrow{\frac{3}{4}} D_3$ $D_3 \xrightarrow{\frac{1}{4}} D_2$
	R _{C₁-5}	$MinThreshold_{C_1} < F_{C_1,D_2,D_1} \leq MaxThreshold_{C_1}$	$D_2 \xrightarrow{\frac{5}{4}} D_1$ $D_1 \xrightarrow{\frac{1}{4}} D_2$		1		R _{C₁-14}	$MinThreshold_{C_1} < F_{C_1,D_2,D_3} \leq MaxThreshold_{C_1}$	$D_2 \xrightarrow{\frac{5}{4}} D_3$ $D_3 \xrightarrow{\frac{1}{4}} D_2$
	R _{C₁-6}	$MaxThreshold_{C_1} < F_{C_1,D_2,D_1}$	$D_2 \xrightarrow{\frac{3}{4}} D_1$ $D_1 \xrightarrow{\frac{1}{4}} D_2$				R _{C₁-15}	$MaxThreshold_{C_1} < F_{C_1,D_2,D_3}$	$D_2 \xrightarrow{\frac{3}{4}} D_3$ $D_3 \xrightarrow{\frac{1}{4}} D_2$
Decision D ₃	R _{C₁-10}	$0 < (F_{C_1,D_2,D_1} = -F_{C_1,D_1,D_2}) \leq MinThreshold_{C_1}$	$D_3 \xrightarrow{\frac{3}{4}} D_1$ $D_1 \xrightarrow{\frac{1}{4}} D_3$	R _{C₁-16}	$0 < (F_{C_1,D_1,D_2} = -F_{C_1,D_2,D_3}) \leq MinThreshold_{C_1}$	$D_3 \xrightarrow{\frac{3}{4}} D_2$ $D_2 \xrightarrow{\frac{1}{4}} D_3$			
	R _{C₁-11}	$MinThreshold_{C_1} < F_{C_1,D_2,D_1} \leq MaxThreshold_{C_1}$	$D_3 \xrightarrow{\frac{5}{4}} D_1$ $D_1 \xrightarrow{\frac{1}{4}} D_3$	R _{C₁-17}	$MinThreshold_{C_1} < F_{C_1,D_2,D_3} \leq MaxThreshold_{C_1}$	$D_3 \xrightarrow{\frac{5}{4}} D_2$ $D_2 \xrightarrow{\frac{1}{4}} D_3$		1	
	R _{C₁-12}	$MaxThreshold_{C_1} < F_{C_1,D_2,D_1}$	$D_3 \xrightarrow{\frac{3}{4}} D_1$ $D_1 \xrightarrow{\frac{1}{4}} D_3$	R _{C₁-18}	$MaxThreshold_{C_1} < F_{C_1,D_2,D_3}$	$D_3 \xrightarrow{\frac{3}{4}} D_2$ $D_2 \xrightarrow{\frac{1}{4}} D_3$			

Appendix A3. Set of expert rules regarding quality of service criterion C_2

	Decision D_1			Decision D_2			Decision D_3								
	RuleId	Condition	Statement	RuleId	Condition	Statement	RuleId	Condition	Statement						
Decision D_1	1			R_{C_2-1}	$0 < (F_{C_2-D_1-D_2} = TTF_{Rof D_1} - TTF_{Rof D_2}) \leq \text{MinThreshold}_{C_2}$	$D_1 \xrightarrow{\frac{3}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_1$	R_{C_2-7}	$0 \leq (F_{C_2-D_1-D_3} = TTF_{Rof D_1} - \text{Thr}_{TTF_{Rof D_1}}) \leq \text{MinThreshold}_{C_2}$	$D_1 \xrightarrow{\frac{3}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_1$						
				R_{C_2-2}	$\text{MinThreshold}_{C_2} < F_{C_2-D_1-D_2} \leq \text{MaxThreshold}_{C_2}$	$D_1 \xrightarrow{\frac{5}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_1$	R_{C_2-8}	$\text{MinThreshold}_{C_2} < F_{C_2-D_1-D_3} \leq \text{MaxThreshold}_{C_2}$	$D_1 \xrightarrow{\frac{5}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_1$						
				R_{C_2-3}	$\text{MaxThreshold}_{C_2} < F_{C_2-D_1-D_2}$	$D_1 \xrightarrow{\frac{7}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_1$	R_{C_2-9}	$\text{MaxThreshold}_{C_2} < F_{C_2-D_1-D_3}$	$D_1 \xrightarrow{\frac{7}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_1$						
Decision D_2				1											
										R_{C_2-4}	$0 < (F_{C_2-D_2-D_1} = -F_{C_2-D_1-D_2}) \leq \text{MinThreshold}_{C_2}$	$D_2 \xrightarrow{\frac{3}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_2$	R_{C_2-13}	$0 \leq (F_{C_2-D_2-D_3} = TTF_{Rof D_1} - \text{Thr}_{TTF_{Rof D_1}}) \leq \text{MinThreshold}_{C_2}$	$D_2 \xrightarrow{\frac{3}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_2$
										R_{C_2-5}	$\text{MinThreshold}_{C_2} < F_{C_2-D_2-D_1} \leq \text{MaxThreshold}_{C_2}$	$D_2 \xrightarrow{\frac{5}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_2$	R_{C_2-14}	$\text{MinThreshold}_{C_2} < F_{C_2-D_2-D_3} \leq \text{MaxThreshold}_{C_2}$	$D_2 \xrightarrow{\frac{5}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_2$
R_{C_2-6}	$\text{MaxThreshold}_{C_2} < F_{C_2-D_2-D_1}$	$D_2 \xrightarrow{\frac{7}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_2$	R_{C_2-15}	$\text{MaxThreshold}_{C_2} < F_{C_2-D_2-D_3}$	$D_2 \xrightarrow{\frac{7}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_2$										
Decision D_3								1							
										R_{C_2-10}	$0 \leq (F_{C_2-D_3-D_1} = -F_{C_2-D_1-D_3}) \leq \text{MinThreshold}_{C_2}$	$D_3 \xrightarrow{\frac{3}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_3$	R_{C_2-16}	$0 \leq (F_{C_2-D_3-D_2} = -F_{C_2-D_2-D_3}) \leq \text{MinThreshold}_{C_2}$	$D_3 \xrightarrow{\frac{3}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_3$
										R_{C_2-11}	$\text{MinThreshold}_{C_2} < F_{C_2-D_3-D_1} \leq \text{MaxThreshold}_{C_2}$	$D_3 \xrightarrow{\frac{5}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_3$	R_{C_2-17}	$\text{MinThreshold}_{C_2} < F_{C_2-D_3-D_2} \leq \text{MaxThreshold}_{C_2}$	$D_3 \xrightarrow{\frac{5}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_3$
R_{C_2-12}	$\text{MaxThreshold}_{C_2} < F_{C_2-D_3-D_1}$	$D_3 \xrightarrow{\frac{7}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_3$	R_{C_2-18}	$\text{MaxThreshold}_{C_2} < F_{C_2-D_3-D_2}$	$D_3 \xrightarrow{\frac{7}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_3$										

Appendix A4. Set of expert rules regarding time criterion C_3

	Decision D_1			Decision D_2			Decision D_3								
	RuleId	Condition	Statement	RuleId	Condition	Statement	RuleId	Condition	Statement						
Decision D_1	1			R_{C_3-1}	$0 < (F_{C_3-D_1-D_2} = RPT_{Rof D_2} - RPT_{Rof D_1}) \leq \text{MinThreshold}_{C_3}$	$D_1 \xrightarrow{\frac{3}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_1$	R_{C_3-7}	$0 < (F_{C_3-D_1-D_3} = \text{WTRL} - RPT_{Rof D_1}) \leq \text{MinThreshold}_{C_3}$	$D_1 \xrightarrow{\frac{3}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_1$						
				R_{C_3-2}	$\text{MinThreshold}_{C_3} < F_{C_3-D_1-D_2} \leq \text{MaxThreshold}_{C_3}$	$D_1 \xrightarrow{\frac{5}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_1$	R_{C_3-8}	$\text{MinThreshold}_{C_3} < F_{C_3-D_1-D_3} \leq \text{MaxThreshold}_{C_3}$	$D_1 \xrightarrow{\frac{5}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_1$						
				R_{C_3-3}	$\text{MaxThreshold}_{C_3} < F_{C_3-D_1-D_2}$	$D_1 \xrightarrow{\frac{7}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_1$	R_{C_3-9}	$\text{MaxThreshold}_{C_3} < F_{C_3-D_1-D_3}$	$D_1 \xrightarrow{\frac{7}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_1$						
Decision D_2				1											
										R_{C_3-4}	$0 < (F_{C_3-D_2-D_1} = -F_{C_3-D_1-D_2}) \leq \text{MinThreshold}_{C_3}$	$D_2 \xrightarrow{\frac{3}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_2$	R_{C_3-13}	$0 < (F_{C_3-D_2-D_3} = \text{WTRL} - RPT_{Rof D_2}) \leq \text{MinThreshold}_{C_3}$	$D_2 \xrightarrow{\frac{3}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_2$
										R_{C_3-5}	$\text{MinThreshold}_{C_3} < F_{C_3-D_2-D_1} = -F_{C_3-D_1-D_2} \leq \text{MaxThreshold}_{C_3}$	$D_2 \xrightarrow{\frac{5}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_2$	R_{C_3-14}	$\text{MinThreshold}_{C_3} < F_{C_3-D_2-D_3} \leq \text{MaxThreshold}_{C_3}$	$D_2 \xrightarrow{\frac{5}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_2$
R_{C_3-6}	$\text{MaxThreshold}_{C_3} < F_{C_3-D_2-D_1}$	$D_2 \xrightarrow{\frac{7}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_2$	R_{C_3-15}	$\text{MaxThreshold}_{C_3} < F_{C_3-D_2-D_3}$	$D_2 \xrightarrow{\frac{7}{2}} D_3$ $D_3 \xrightarrow{\frac{1}{2}} D_2$										
Decision D_3								1							
										R_{C_3-10}	$0 < (F_{C_3-D_3-D_1} = -F_{C_3-D_1-D_3}) \leq \text{MinThreshold}_{C_3}$	$D_3 \xrightarrow{\frac{3}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_3$	R_{C_3-16}	$0 < (F_{C_3-D_3-D_2} = -F_{C_3-D_2-D_3}) \leq \text{MinThreshold}_{C_3}$	$D_3 \xrightarrow{\frac{3}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_3$
										R_{C_3-11}	$\text{MinThreshold}_{C_3} < F_{C_3-D_3-D_1} \leq \text{MaxThreshold}_{C_3}$	$D_3 \xrightarrow{\frac{5}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_3$	R_{C_3-17}	$\text{MinThreshold}_{C_3} < F_{C_3-D_3-D_2} \leq \text{MaxThreshold}_{C_3}$	$D_3 \xrightarrow{\frac{5}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_3$
R_{C_3-12}	$\text{MaxThreshold}_{C_3} < F_{C_3-D_3-D_1}$	$D_3 \xrightarrow{\frac{7}{2}} D_1$ $D_1 \xrightarrow{\frac{1}{2}} D_3$	R_{C_3-18}	$\text{MaxThreshold}_{C_3} < F_{C_3-D_3-D_2}$	$D_3 \xrightarrow{\frac{7}{2}} D_2$ $D_2 \xrightarrow{\frac{1}{2}} D_3$										

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